Impact of a Creativity Support Tool on Student Learning about Scientific Discovery Processes

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Abstract

Science education nowadays emphasizes authentic science practices mimicking the creative discovery processes of real scientists. How, then, can we build creativity support tools for student learning about scientific discovery processes? We summarize several epistemic views of ideation in scientific discovery and find that the ideation techniques provide few guarantees of correctness of scientific hypotheses, indicating the need for supporting hypothesis evaluation. We describe an interactive tool called MILA–S that enables students to elaborate hypotheses about ecological phenomena into conceptual models and evaluate conceptual models through agent-based simulations. We report on a pilot experiment with 50 middle school students who used MILA–S to discover causal explanations for an ecological phenomenon. Preliminary results from the study indicate that use of MILA–S had a significant impact both on the creative process of model construction and the nature of the constructed models. We posit that the computational support for model construction, evaluation and revision embodied in MILA–S fosters student creativity in learning about scientific discovery processes.

Introduction

Scientific discovery in general is a creative task (Carruthers, Stitch & Siegal 2002; Clement 2008; Darden 1998; Magini, Nersessian & Thagard 1999; Nersessian 2008). Thus, computational modeling of scientific discovery processes has received significant attention in AI research on creativity (Chen et al. 2009; Davies, Nersessian & Goel 2005; Griffith, Nersessian & Goel 2000; Langley 2000; Langley et al. 1987; Lindsay et al. 1980). Science education nowadays emphasizes authentic science practices mimicking the creative discovery processes of real scientists (Clement 2008; Edelson et al. 1999). Thus, interactive tools for supporting authentic science practices in science education have received significant attention in AI research on education (Bridewell et al. 2006; De Jong & van Joolingen 1998; Jackson, Krajcik, & Soloway 2000; Novak 2010; vanLehn 2013).

The goal of supporting creative discovery processes in science education raises several issues for research on computational creativity. We briefly three questions:
(1) What specific tasks in creative discovery processes should we automate in supporting science education? We focus on ideation in scientific discovery, and summarize five epistemic views of ideation in the literature. We find that most epistemic views provide few guarantees of the correctness of ideas. This indicates a need for supporting hypothesis evaluation in student learning about creative discovery processes.
(2) What computational tools may support evaluation of hypotheses in science education? We focus on conceptual modeling in scientific discovery. We summarize an interactive technology called MILA−S for first elaborating explanatory hypotheses into conceptual models and then evaluating a hypothesis through simulation.
(3) What is the impact of creativity support tools such as MILA−S on student learning about scientific discovery processes? We summarize an educational intervention in a middle school engaging MILA−S for modeling ecological phenomena. We find that the use of MILA−S had substantial impact on the discovery processes of middle school students in modeling the ecological phenomenon.

Epistemic Views of Scientific Discovery

Idea generation is a core element of the creative process in scientific discovery (Clement 2008; Nersessian 2008). However, the task of ideation is complex. The question for us is what specific subtasks of ideation should we automate in supporting student learning about scientific discovery processes? To answer this question, we examine several epistemic views of ideation in scientific discovery.

Conceptual Classification

One common view of ideation in scientific discovery is classification of data into known categories.. We know about Linneas' classic work on classification in biology. Classification continues to be important in modern biology (e.g., Golub et al. 1999). Classification has been extensively studied in AI (e.g., Duda, Hart & Stork 2001) and ML (e.g., Bishop 2007). The classic DENDRAL system (Lindsay et al. 1980) classified mass spectroscopy data into chemical molecules. Chandrasekaran & Goel (1988) trace the evolution of early AI theories of classification. We have studied both top-down hierarchical classification in which a concept is incrementally refined based on data (Goel, Soundarajan & Chandrasekaran 1987), and bottom-up hierarchical classification in which features of data are incrementally abstracted into a concept (Bylander, Goel & Johnson 1991).

Abductive Explanation

Abductive inference, i.e., inference to the best explanation for a set of data, is another common view of ideation in scientific discovery. AI has studied abduction from multiple perspectives (e.g., Charniak & McDermott 1985; Josephson & Josephson 1996). The classic BACON system (Langley et al. 1987) abduced physical laws from data. Bylander et al. (1991) have analyzed the computational complexity of the abduction task. Goel et al. (1995) describe a computational technique for abductive explanation based on the RED system for identifying red-cell antibodies in a patient's serum (Fischer et al 1991): the technique assembles composite explanations that explain a set of data from elementary explanations that explain subsets of the data.

Conceptual Modeling

Conceptual modeling is ubiquitous in science (e.g., Clement 2008; Darden 1998; Nersessian 2008). Conceptual models are abstract representations of the elements, relationships, and processes of a complex phenomenon or system. AI has extensively studied conceptual models (e.g., Davis 1990; Lenat 1995; Stefik 1995). We have developed conceptual models of complex systems that specify how a system works, i.e., the way the system's structure produces its behaviors that achieve its functions (Goel, Rugaber & Vattam 2009). We have used structure-behavior-function modeling for both engineering systems (Goel & Bhatta 2004) and natural systems (Goel et al. 2012) for supporting a variety of reasoning processes in design and invention.

Analogical Reasoning

Scientific discovery often engages analogical reasoning (Clement 2008; Dunbar 1997; Nersessian 2008). We know about Neil Bohr's famous analogy between the atomic structure and the solar system. Analogical reasoning engages retrieval of an analogue useful for addressing the scientific problem of interest and transfer of the relevant relational knowledge from the retrieved analogue to the scientific problem. AI research has developed several theories of analogical reasoning (e.g., Bhatta & Goel 2004; Falkanehainer, Forbus & Gentner 1989; Hofstader 1996; Thagard et al. 1990). We have studied analogical reasoning in scientific problem solving (Griffith, Nersessian & Goel 2000). Starting from verbal protocols of physicists addressing problems with spring systems (Clement 1988), we developed an AI system called Torque that emulates the problem solving behavior of the physicists.

Visual Reasoning

Scientific discovery often engages visual representations and reasoning (Clement 2008; Magnini, Nersessian & Nersessian 1999; Nersessian 2008). Although some AI research has explored visual representations and reasoning (e.g., Glasgow, Narayanan & Chandrasekaran 1995), AI research on visual representations and reasoning is not as robust or mature as on, say, classification. We have developed a language for representing visual knowledge and a computational technique for reasoning about visual analogies (Davies, Goel & Yaner 2008), and to understand the use of visual analogy Maxwell's construction of the unified theory of electromagnetism (Davies, Nersessian & Goel 2005).

The Evaluation Task

It is noteworthy that in general the above methods of idea generation in scientific discovery provide few guarantees of correctness of their results. Further, while these methods help generate hypotheses for a given situation, in general they do not by themselves evaluate their results. This indicates a need for supporting hypothesis evaluation in student learning about creative discovery processes. That is, there is a need for developing interactive tools that automate the evaluation task in the context of supporting creativity in student learning about scientific discovery processes. Thus, we decided to focus on automating the evaluation task in supporting student learning as described below.

Model Construction and Evaluation

In this work, we elected to automate the evaluation task in the context of supporting creativity in student learning about conceptual modeling. Cognitive science theories of scientific discovery describe scientific modeling as an iterative process entailing four related but distinct phases: model construction, use, evaluation, and revision (Clement 2008; Nersessian 2008; Schwarz et al. 2009). Thus, a model is first constructed to explain some observations of a phenomenon. The model is then used to make predictions about other aspects of the phenomenon. The model's predictions next are evaluated against actual observations of the system. Finally, the model is revised based on the evaluations to correct the errors and improve the model's explanatory and predictive efficacy.

Scientific models can be of several different types, with each model type having its own unique affordances and constraints, and fulfilling specific functional roles in scientific inquiry (Carruthers, Stitch & Siegal 2002; Magnini, Nersessian & Thagard 1999). In this work, we are specifically interested in two kinds of models: conceptual models and simulation models. Conceptual models allow scientists to specify and share explanations of how a system works, aided by the semantics and structures of the specific conceptual modeling framework. Conceptual models tend to rely heavily on directly modifiable representations, languages and visualizations, enabling rapid iterations of the model construction cycle.

Simulation models capture relationships between the variables of a system such that as the values of input variables are specified, the simulation model predicts the temporal evolution of the values of other system variables. Thus, the simulation model of a system can be run repeatedly with different values for the input variables, the predicted values of the system variables can be compared with the actual observations of the system, and the simulation model can be revised to account for discrepancies between the predictions and the observations. A main limitation of simulation models is the complexity of the setting up a simulation, which makes it difficult to rapidly iterate on the model construction cycle.

AI research on science education has used both conceptual models (e.g., Novak 2010; vanLehn 2013) and simulation models (e.g., Bridewell et al. 2006; de Jong & van Joolingen 1998; Jackson, Krajcik, & Soloway 2000) very extensively and quite productively. However, AI research on science education typically uses the two kinds of models independently from each other: students use one set of tools for constructing, using, and revising conceptual models, and another tool set for constructing and using simulation models. However, cognitive science theories of scientific inquiry suggest a symbiotic relationship between conceptual modeling and simulation modeling (e.g., Clement 2008; Magnini, Nersessian & Thagard 1999; Nersessian 2008): scientists use conceptual models to set up the simulation models, and they run simulation models to test and revise the conceptual models. Thus, we developed an interactive system called MILA–S that enables science students to construct conceptual models of ecosystems, to directly and automatically generate simulation models from the conceptual models, and then execute the simulations.

MILA−S: A Tool for Model Construction and Evaluation

MILA (**M**odeling & **I**nquiry **L**earning **A**pplication)_ is a family of interactive tools for supporting student learning about scientific discovery. The core MILA tool enables middle school students to investigate and construct models of complex ecological phenomena. MILA–S also allows students to simulate their conceptual models (Joyner, Goel & Papin 2014). In this paper, we focus on the impact of using MILA-S on students' creativity in conceptual modeling.

MILA builds on a line of exploratory learning environments including the Aquarium Construction Toolkit (ACT; Vattam et al. 2011) and the Ecological Modeling Toolkit (EMT; Joyner et al. 2011). ACT and EMT were shown to facilitate significant improvement in students' deep, expert-like understanding of complex ecological systems. For conceptual modeling, ACT used Structure-Behavior-Functions models that were initially developed in AI research on system design (Goel, Rugaber & Vattam 2009). In contrast, EMT used Component-Mechanism-Phenomenon (or CMP) conceptual models that are variants of Structure-Behavior-Function models adapted for modeling ecological systems. Both ACT and EMT used NetLogo simulations as the simulation models (Wilsensky & Reisman 2006; Wilensky & Resnick 1999). Like most interactive tools for supporting modeling in science education (vanLehn 2013), both ACT and EMT provided one set of tools for constructing and revising conceptual models and another tool set for using simulations.

Like EMT, MILA–S uses Component-Mechanism-Phenomenon (or CMP) conceptual models that are variants of the Structure-Behavior-Function models used in ACT.. In CMP models, mechanisms explain phenomena such as fish dying in a lake. Mechanisms arise out of interactions among components and relations among them. Components are parts of the physical structure of system, and are classified as either biotic or abiotic; oxygen, for example, is an abiotic component while fish are biotic components. The representation of each component in CMP includes a set of variables such as population, age, birth rate, and energy for biotic components, and amount for abiotic components. The representation of each component is annotated by a set of parameters specifically for setting up a simulation, such as the appearance of the component and ranges for each variable associated with the component.

In the CMP model of a system, representations of components (and their variables) are related together through different kinds of relations. MILA–S provides the modeler with a set of prototype relations. For example, interactions between a biotic component like 'Fish' and an abiotic component like 'Oxygen' could be 'consumes', 'produces', or 'destroys'. Connections have directionality; a connection from 'Oxygen' to 'Fish' would have a different set of prototypes, including 'poisons'. Representations of relations are also annotated with parameters to facilitate the simulation, such as energy provided for 'consumes' and rate of production for 'produces'.

Like ACT and EMT, MILA–S too uses the NetLogo simulation infrastructure. After constructing a CMP conceptual model, a student clicks a 'Run Sim' button to initialize MILA–S and pass their model for simulation generation. MILA–S iterates through some initial boilerplate settings, then gathers together all the components for initialization along with their individual parameters. After this, MILA–S writes the functions based on the relations specified in the CMP model. A key part of this is a set of assumptions that MILA–S makes about the nature of ecological systems. For example, MILA–S assumes that if a biotic component consumes a certain other component, then it must need that other component to survive. A model with 'Fish' that contains 'consumes' connections to both 'Plankton' and 'Oxygen' would infer that fish need both Plankton and Oxygen to survive. MILA–S also assumes that species will continue to reproduce to fulfill their carrying capacity rather

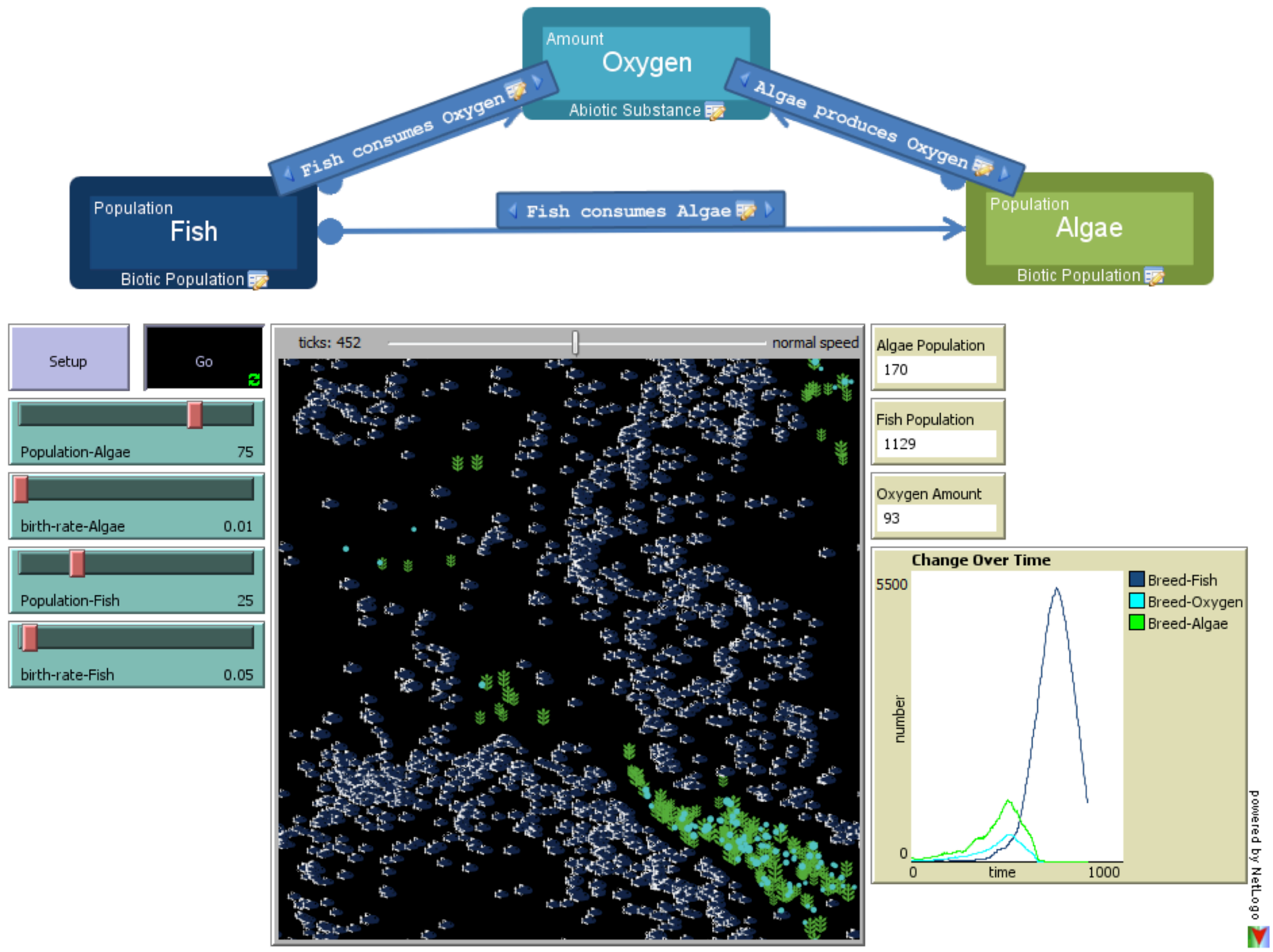

Figure 1: A model in MILA–S (top) showing a set of simple relationships between fish, algae, and oxygen, and the NetLogo simulation (bottom) generated by MILA–S to simulate the model. This model was constructed by the team described in the third case study below; the simulation was generated and run from their model by research staff to obtain this screenshot.

than hitting other arbitrary limitations. These assumptions do limit the range of simulations that MILA–S can generate, but they also facilitate the higher-level rapid model revision process that is the learning objective of this project. Figure 1 illustrates a simple conceptual model constructed by a middle school student team (on the top of the figure) and the results of simulating it (at the bottom).

Educational Intervention

The present intervention had two main parts. In the first part, 10 classes with 237 students in a metro Atlanta middle school used MILA for two weeks. During this time, students worked in small teams of two or three to investigate two phenomena: a recent massive and sudden fish death in a nearby lake and the record high temperatures in the local area over the previous decade. In the second part, two classes with 50 of the original 237 students used MILA-S to more deeply investigating the phenomenon of massive, sudden death of fish in the lake.

Prior to engagement with MILA–S, the 50 students in our study received a two-week curriculum on modeling and inquiry, featuring five days of interaction with CMP conceptual modeling in MILA. In the first part of the study using MILA, students also used pre-programmed NetLogo simulations that did not respond to students' models, but nonetheless provided students experience with the NetLogo interface and toolkit. Thus, when given MILA–S, students already had significant experience with CMP conceptual modeling, NetLogo simulations, and the interface of MILA−S. The question now becomes what was the impact of using MILA−S on students' creativity?

Impact on Students' Creativity

An initial examination of the processes and results of model construction by the student teams in our study provides two insights. Firstly, there exists a fundamental difference in the conceptual models that students constructed with MILA–S compared to the earlier models they constructed with MILA: while earlier models were retrospective and explanatory, models constructed with MILA–S models were prospective and dynamic. Secondly, the model construction process when students were equipped with MILA–S was profoundly different from their earlier process using MILA: whereas previously, conceptual models were used to guide investigation into sources of information such as existing theories or data observations, once equipped with MILA–S the students used the conceptual models to spawn simulations that directly tested the implications of their hypotheses and models thereof.

The Constructed Models

During engagement with MILA, students produced models that can be described as retrospective and explanatory. Students started from an observable phenomenon, the aforementioned fish kill, and recounted a series of events that led to that result. Causal relationships were captured throughout the model, but only those that lay directly in the causal path leading to the observed phenomenon, and only in the specific way in which the chain occurred in the phenomenon. For example, one team modeled multiple feedback cycles to explain the phenomenon. In their model, a heat spike caused algae populations to grow out of control, then die off due to a lack of carbon dioxide to breathe and a lack of sunlight to produce energy (due to the thick algae clouding the lake). This led to a spike in algae-decomposing bacteria who suddenly had an ample food supply, as well as a drop in the population of oxygen-producing algae. These bacteria, then, consumed an enormous quantity of oxygen, causing the fish population to suffocate. This led to more dead matter in the lake, thus encouraging more bacteria reproduction, exacerbating the fish kill further.

This model presented a complete explanation for why and how the fish kill occurred in the lake; however, the model only captured a retrospective view of the series of events applicable in this situation. Although students could use mental simulation to imagine the results, these models do not explicitly capture dynamic relationships in the system, and thus are of limited use describing what would have happened under different circumstances. For example, had the temperature changed more slowly and allowed the algae to grow steadily rather than exploding and plummeting in quick succession, could the lake have sustained the increased algae population? Would the increased algae population have produced sufficient oxygen to allow the fish population to grow and thrive as well? Thus, models constructed with MILA were explanatory and retrospective.

With MILA–S, students constructed fundamentally different kinds of models that aimed not to capture the series of events that occurred, but rather to capture the dynamic relationships that gave rise to that series of events. Thus, the models constructed in MILA–S invoked a layer of abstraction and generalization away from the models constructed in MILA. For example, one team constructed an initial model that captured the three relationships they considered most pertinent in the system. These students already believed that the fish kill was caused by a sudden drop in oxygen, thus suffocating the fish. Thus, their first relationship was that fish consume oxygen. They similarly knew that oxygen is produced from sunlight, and thus included the relationship between sunlight and oxygen. These connections differed fundamentally from those modelled in MILA, such as accounting for trends in multiple directions (i.e. oxygen production varies directly, up or down, with sunlight presence). The model was not constructed to directly explain the phenomenon, but rather to provide the relationships necessary so that under the right conditions, the phenomenon may arise on its own.

Model Construction Process

During prior engagement with MILA, model construction occurred as students constructed their initial hypotheses, typically connecting only a cause to a phenomenon with no mechanism in between. This was then used to guide investigation into other sources of information such as observed data or other theories to look for corroborating observations or similar phenomena. The conceptual model was then evaluated according to how well it matched the findings; in some cases, the findings directly contradicted the model, while in other cases, the findings lent evidence or mechanism to the model. Finally, the conceptual models were revised in light of this new information (or dismissed in favor of stronger hypotheses, reflecting revision at a higher level) and the process began again.

During engagement with MILA–S, however, we observed a profound variation on the model construction process. The four phases of model construction were still present, but the nature of model use and evaluation changed. Students started by constructing a small number of relationships they believe to be relevant in the system, the model construction phase. After some initial debugging and testing to become familiar with the way in which conceptual models and simulations fit together, students generated simulations and used them to test the implications of their conceptual models. After running the simulation a few times, students then evaluated how well the results of the simulation matched the observations from the phenomenon. This evaluation had two levels: first, did the simulation accurately predict the ultimate phenomenon (in this case, the fish kill)? Once this basic evaluation was met, an advanced evaluation followed: did other variables, trends, and relationships in the simulation match other observations from the phenomenon? For example, one team successfully caused a fish kill by causing the quantity of food available to the fish to drop, but evaluated this as a poor model nonetheless because nothing in the system indicated a disturbance to the fish's food supply. Finally, equipped with the results of this evaluation, students revised their models to more closely approximate the actual system.

Thus, students still constructed and revised conceptual models, but through the simulation generation framework of MILA–S, the model use and evaluation stages took on the practical rigor, repeatable testing, and numeric analysis facilitated by simulations. Rather than speculating on the extent to which their model could explain a phenomenon, students were able to directly test its predictive power. Then, when models were shown to lack the ability to explain the full spectrum of the phenomenon, students were able to quickly return and revise their conceptual models and iterate through the process again.

Three Illustrative Case Studies

We present three case studies from our experiment to illustrate the above observations about the model construction process. These case studies were chosen to demonstrate variations in the process and connections to the underlying model of construction and revision.

Case 1

The first team posited that pollution from dangerous chemicals played a significant role in the system. Specifically, this team speculated that chemicals were responsible for killing the algae in the lake, which then caused the fish population to drop. They began this hypothesis by constructing a model suggesting that algae produces oxygen, fish consume oxygen, and harmful chemicals destroy algae populations. They then used MILA–S to generate and use a simulation of this model to mimic the initial conditions present in the system (i.e. a fish population, an algae population, and an influx of chemicals). This simulation showed the growth of fish population continuing despite the dampened growth of algae population from the harmful chemicals. The team evaluated this to mean that the death of algae alone could not cause the massive fish kill to occur. The team then revised their model to suggest chemicals directly contributed to the fish kill by poisoning the fish directly, as well as killing the algae.

The team then used MILA–S to generate another simulation. This time, when the team used the simulation under similar initial conditions, the fish population initially grew wildly, but the chemicals ate away at both the fish and algae. Eventually, the harmful chemicals finished eating away at the algae, the oxygen quantity plummeted, and the fish suffocated. Students evaluated that this simulation matched the observed phenomenon, but also evaluated that their model missed a relevant relation: based on a source present in the classroom, students posited that fish ought to consume algae. They revised their model to account for this error uncovered during evaluation, used their simulation again, found the same result, and evaluated that they had provided a model that could explain the fish kill.

Case 2

A second team started off by creating a simple set of relations that they believed was present due to their biology background and prior experience with MILA. First, they speculated that sunlight "produces" oxygen, and then that fish, in turn, consume the oxygen. Following these two initial relationships, they generated their first simulation through MILA–S and used it to mimic the believed initial conditions of the lake (i.e. a population of fish, available oxygen, available sunlight). Sunlight was inferred to be continuously available, and thus, at first, the population of fish expanded continuously without any limiting factor. However, when the population of fish hit a certain threshold, it began to consume oxygen faster than it was being produced. This led to the quantity of oxygen dropping, and subsequently, the population of fish dropping. However, rather than depleting completely, the fish and oxygen populations instead began to fluctuate inversely, with oxygen concentration rebounding sufficiently when fish population dropped, allowing the fish to rebound.

The team ran this simulation multiple times to ensure that this trend repeated itself. In one instance, the fish population crashed on its own simply due to the suddenness of the fish population growth and subsequent crash. However, the team evaluated that this was not an adequate explanation of what had actually happened in the lake. The team posited that if this kind of expansion and crash could happen without outside forces, it would be more common. Second, the team observed that their model contained faulty or questionable claims, such as the notion that sunlight "produces" algae. This evaluation based on both the simulation results and reflection on the model led to a phase of revision. An 'Algae' component was added between sunlight and oxygen, representing photosynthesis. Students then used MILA–S to generate a new simulation, and used this new simulation to test the model. This time, students found that their model posited that an oxygen crash would *always* occur in the system, and evaluated that while this successfully mimicked the phenomenon of interest, it failed to match the lake on other days.

Case 3

The third team began with an interesting hypothesis: algae serves as both the food for fish and the oxygen producer for fish. The team, thus, started with a simple three-component model with fish, algae, and oxygen: fish consume algae, fish consume oxygen, and algae produces oxygen. The team further posited that in order for algae populations to grow, they must have sunlight to feed their photosynthesis process. Sunlight, therefore, was drawn to produce algae. The team reasoned that if the fish population destroys the source of one type of 'food' (oxygen) in search for another type (actual food), it could inadvertently destroy its only source for a necessary nutrient.

The team used MILA–S to generate a simulation based on this model and ran it several times under different initial conditions. Each time, algae population initially grew due to the influx of sunlight. As a result, fish populations grew, due to the abundance of both algae (as produced via sunlight) and oxygen (as produced by the algae). As the fish population spiked, the algae hit a critical point where it began to be eaten faster than it reproduced, and the rate of sunlight entering the system was insufficient to maintain steady, strong growth. This caused the algae population to plummet, and in turn, the fish population to plummet as the fish suddenly lacked both food and oxygen. Sometimes, the algae population subsequently bounced back even after the fish fully died off, while in others both species died entirely.

Unlike the second team, this third team evaluated this to mean their model was accurate: under the initial conditions observed in the lake, their model predicted an algal bloom every single time. Thus, the third team provided two interesting variations on the model construction process observed in other teams: first, they overloaded one particular component, demonstrating an advanced notion of how components can play multiple functional roles. Second, they posited that a successful model would predict that the same events would transpire under the same initial conditions every time, as opposed to the second team's notion that this phenomenon ought to only occur sometimes.

Summary, Conclusions, and Future Work

Scientific discovery in general is a creative task. Our goal in this work was to enable science students to mimic the scientific modeling practices of real scientists and thus help make learning about scientific discovery as authentic as possible. Our analysis of several epistemic views of idea generation in scientific discovery indicated a need for automating the task of hypothesis evaluation. Therefore, we developed an interactive system called MILA–S that enables science students to construct conceptual models of ecosystems, to directly evaluating the conceptual models by automatically generating simulation models from the conceptual models and then execute the simulations. Our hypothesis was that the computational support for model construction and evaluation embodied in MILA–S would foster student creativity in scientific modeling.

Initial results from a pilot study with 50 students in a middle school provide preliminary evidence in favor of the hypothesis (although a controlled study is needed to conclusively verify these claims). Firstly, students approached the modeling process from a different perspective from the outset, striving to capture dynamic relationships among the components of the ecological system. These dynamic relationships then promoted a more abstract and general perspective on the system. Secondly, the process of model construction, use, evaluation, and revision presented itself naturally during this intervention, with the simulations playing a key role in supporting the cyclical process of constructing conceptual models. By using the simulations to test their predictions and claims, and by subsequently evaluating the success of their conceptual models by matching observations from the actual phenomenon, students engaged in a rapid feedback cycle that saw rapid model revision and repeated use for continued evaluation. MILA–S empowers science students to evaluate the conceptual models through simulation, allowing them to focus on idea generation, and model construction and revision.

Note that in addition to conceptual modeling, this project entails some of the other processes of scientific discovery we briefly mentioned in the introduction. Thus, it engages abductive explanation as students explore multiple hypotheses for explaining an ecological phenomenon, and construct the best explanation for the given data about the phenomenon. It also engages visual representations and reasoning: students construct a visual representation of their conceptual model of the ecological phenomenon (top of Figure 1) and generate visualizations of simulations directly from the conceptual models (bottom of Figure 1).

We are presently engaged in a full-scale investigation to test these theories, techniques and tools with college-level biology students. The objective of this investigation is to examine the use of creativity support tools for scientific modeling of ecological phenomena in college-level introductory biology courses.

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References

Bishop, C. (2007) *Pattern recognition and Machine Learning.* Springer.

Bridewell, W., Sanchez, J., Langley, P., & Billman, D. (2006) An Interactive Environment for Modeling and Discovery of Scientific Knowledge. *IJHMS* 64(11): 1099-1114.

Bylander, T., Allemang, D., Tanner, M., & Josephson, J. (1991) The Computational Complexity of Abduction. *Artificial Intelligence* 49: 25-60.

Bylander, T., Johnson, T., & Goel, A. (1991) Structured Matching: A Task-Specific Technique for Making Decisions. *Knowledge Acquisition* 3(1):1-20.

Carruthers, P., Stitch, S., & Siegal, M. (editors, 2002) *The Cognitive Basis of Science*, Cambridge University Press.

Chandrasekaran, B., & Goel, A. (1988) From Numbers to Symbols to Knowledge Structures: Artificial Intelligence Perspectives on the Classification Task. *IEEE Transactions on Systems, Man, and Cybernetics* 18(3): 415-424.

Charniak, E., & McDermott, D. (1985) *Artificial Intelligence.* Addison-Wesley.

Chen, C., Chen, Y,, Horowitz, M., Hou, H., Liu, Z., & Pellegrino, D. (2009) Towards an Explanatory and Computational Theory of Scientific Discovery, Infometrics 3(3): 191-209.

Clement, J. (1988) Observed Methods of Generating Analogies in Scientific Problem Solving. *Cognitive Science* 12: 563-586.

Clement, J. (2008). *Creative Model Construction in Scientists and Students: The Role of Imagery, Analogy, and Mental Simulation*. Dordrecht: Springer.

Darden, L. (1998). Anomaly-driven theory redesign: computational philosophy of science experiments. In T. W. Bynum, & J. Moor (Eds.), *The Digital Phoenix: How Computers are Changing Philosophy* (pp. 62–78). Oxford: Blackwell.

Davies, J., Goel, A., & Yaner, P. (2008) Proteus: A Theory of Visual Analogies in Problem Solving. *Knowledge-Based Systems* 21(7): 636-654.

Davies, J., Nersessian, N., & Goel, A. (2005) Visual Models in Analogical Problem Solving. *Foundations of Science* 10(1): 133-152.

Davis, E. (1990) *Representations of Commonsense Knowledge.* Morgan Kauffman.

De Jong, T., & Van Joolingen, W. (1998). Scientific discovery learning with computer simulations of conceptual domains. *Review of Educational Research, 68*(2), 179-201.

Duda, R., Hart, P., & D. Stork. (2001) *Pattern Classification.* 2nd Edition. John Wiley.

Dunbar, K. (1997) How scientists think: Online creativity and conceptual change in science. In Ward, Smith, & Vaid (Editors), *Conceptual structures and processes: Emergence discovery and change* (pp. 461–493). Washington, DC: American Psychological Association.

Edelson, D., Gordin, D., & Pea, R. (1999). Addressing the challenges of inquiry-based learning through technology and curriculum design. *Journal of the Learning Sciences, 8*(3-4), 391-450.

Falkenhainer, B., Forbus, K., & Gentner, D. (1989) The Structure-Mapping Engine: Algorithms and Examples. *Artificial Intelligence* 41(1): 1-63.

Fischer, O., Goel, A., Svirbely, J., & Smith, J. (1991) The Role of Essential Explanations in Abduction. *Artificial Intelligence in Medicine* 3: 181-191.

Glasgow, J., Narayanan, N.H., Chandrasekaran, B. (Editors, 1995) *Diagrammatic Reasoning: Cognitive and Computational Perspectives*, MIT Press.

Goel, A., & Bhatta, S. (2004) Use of Design Patterns in Analogy-Based Design. *Advanced Engineering Informatics* 18(2):85-94.

Goel, A., Josephson, J., Fischer, O., & Sadayappan, P. (1995) Practical Abduction: Characterization, Decomposition and Distribution. *Journal of Experimental and Theoretical Artificial Intelligence* 7: 429-450.

Goel, A., Rugaber, S., & Vattam, S. (2009). Structure, Behavior & Function of Complex Systems: The SBF Modeling Language. *AI for Engineering Design, Analysis and Manufacturing,* 23: 23-35.

Goel, A., Soundararajan, N., & Chandrasekaran, B. (1987) Complexity in Classificatory Reasoning. In *Proc. Sixth National Conference on Artificial Intelligence (AAAI-87),* Seattle, July 1987, 421-425.

Goel, A., Vattam, S., Wiltgen, B., & Helms, M. (2012) Cognitive, Collaborative, Conceptual and Creative - Four Characteristics of the Next Generation of Knowledge-Based CAD Systems: A Study in Biologically Inspired Design. *Computer-Aided Design*, 44(10): 879-900.

Golub, T., Slonim, D., Tamayo, P. et al. (1999) Molecular classification of cancer: class discovery and class prediction by gene expression monitoring. *Science* 289(5439): 531-537.

Griffith, T., Nersessian, N., & Goel, A. (2000) Function-follows-Form: Generative Modeling in Scientific Reasoning. In *Proc. Twenty Second Conference of the Cognitive Science Society*, Philadelphia, pp. 196-201.

Hofstadter, D (Editor, 1996) *Fluid concepts and creative analogies: Computer models of the fundamental mechanisms of thought*, Basic Books, New York.

Jackson, S., Krajcik, J., & Soloway, E. (2000) Model-It: A Design Retrospective. In M. Jacobson & R. Kozma (editors), *Innovations in Science and Mathematics Education: Advanced Designs for Technologies of Learning* (pp. 77-115). Lawrence Erlbaum.

Josephson, J., & Josephson, S. (editors, 1996) *Abductive Inference: Computation, Philosophy, Technology*. Cambridge University Press.

Joyner, D., Goel, A., Rugaber, S., Hmelo-Silver, C., & Jordan, R. (2011). Evolution of an Integrated Technology for Supporting Learning about Complex Systems. In *Proc. 11th IEEE International Conference on Advanced Learning Technologies*, Athens, GA.

Joyner, D., Goel, A., & Papin, N. (2014). MILA–S: Generation of Agent-Based Simulations from Conceptual Models of Complex Systems. In *Procs. 19th International Conference on Intelligent User Interfaces*, Haifa, Israel.

Langley, P. (2000) The Computational Support of Scientific Discovery. *IJHMS* 53(3): 393-410.

Langley, P., Simon, H., Bradshaw, G., & Zytkow, J. (Editors, 1987) *Scientific Discovery: Computational Explorations of the Creative Process*. Cambridge, MA: MIT Press, 1987.

Lenat, D. (1995) CYC: A Large-Scale Investment in Knowledge Infrastructure. *Communications of ACM* 58(11): 32-38.

Lindsay, R., Buchanan, B., Feigenbaum, E., & Lederberg, J. (Editors, 1980) *Applications of Artificial Intelligence for Organic Chemistry: The DENDRAL Project.* McGraw-Hill.

Magnini, L., Nersessian, N., & Thagard, P. (editors, 1999) *Model-Based Reasoning in Scientific Discovery*. Kluwer.

Nersessian, N. (2008). *Creating Scientific Concepts*. Cambridge, MA: MIT Press.

Novak, J. (2010) *Learning, Creating and Using Knowledge: Concept Maps as Facilitative Tools in Schools and Corporations*. New York: Routledge.

Schwarz, C., Reiser, B., Davis, E., Kenyon, L., Achér, A., Fortus, D., Shwartz, Y., Hug, B., & Krajcik, J. (2009). Developing a learning progression for scientific modeling: Making scientific modeling accessible and meaningful for learners. *Journal of Research in Science Teaching, 46*(6), 632-654.

Stefik, M. (1995) *Knowledge Systems.* Morgan Kauffman.

Thagard, P., Holyoak, K. J., Nelson, G., & Gochfeld, D. (1990). Analog retrieval by constraint satisfaction. *Artificial Intelligence*, 46, 259-310.

VanLehn, K. (2013). Model construction as a learning activity: a design space and review. *Interactive Learning Environments*, *21*(4), 371-413.

Vattam, S., Goel, A., Rugaber, S., Hmelo–Silver, C., Jordan, R., Gray, S, & Sinha, S. (2011) Understanding Complex Natural Systems by Articulating Structure- Behavior-Function Models. *Journal of Educational Technology & Society, 14*(1): 66-81.

Wilensky, U., & Reisman, K. (2006). Thinking Like a Wolf, a Sheep, or a Firefly: Learning Biology Through Constructing and Testing Computational Theories-An Embodied Modeling Approach. *Cognition and Instruction, 24*(2), 171-209.

Wilensky, U., & Resnick, M. (1999). Thinking in levels: A dynamic systems approach to making sense of the world. *Journal of Science Education and Technology*, 8, 3-19.